A Feature Extraction Algorithm of Underwater Acoustic Target Based on LOFAR Distribution

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Abstract: As one of primary analysis approaches of passive sonar signals, LOFAR (Low Frequency Analysis and Recording) spectrum has been used in underwater acoustic target detection, tracking, classification, etc. However, spectral components of underwater acoustic signals are complex, because the signals may be affected by sea features and noise radiated from targets. As a consequence, the passive sonar signals are not stationarity, and the result of detection with LOFAR spectrum is not ideal, against background noise. Therefore, this paper proposes an algorithm of feature extraction based on LOFAR spectral distribution (FELSD), in order to improve the performance of underwater acoustic target on classification. The proposed algorithm is evaluated in a real dataset collected by a passive sonar system that has been installed in a submarine, and experiments show that our algorithm has higher accuracy of classification (supervised and unsupervised), compared with traditional methods.

1. Introduction

Basic sonar systems can be divided into two categories: active and passive that in the active type, by sending sound pulses and analyzing their echoes, the type, distance and direction of the target can be identified[1]. In passive sonar, underwater acoustic signals received by the array of hydrophones, and targets can be classified by analyzing the content of the signals after preprocessing[2-3]. Compared with active sonar systems, passive sonar systems are widely deployed because of their concealment and confidentiality in practical marine activities. In order to detect and classify underwater acoustic target, relevant spectral features of target are often obtained from a given direction. There are two types of spectral analysis that can be implement to extract relevant spectral features of acoustic target: DEMON (Detection Envelope Modulation On Noise) and LOFAR (Low Frequency Analysis and Recording)[4]. The DEMON is a narrowband analysis that can identified propeller characteristic[5]. The LOFAR, which provides line spectral features of frequency power versus time, is a broadband analysis estimating the noise characteristic of the target machinery. Given the discreteness of the source, the noise ratio is relatively low, LOFAR is more suitable for target detection [6-7].

However, the spectral components of underwater acoustic signals are complex, because underwater acoustic signals may be affected by sea features (salinity, depth, and so on) and noise (machinery noise of engine) radiated from targets. On the other hand, Doppler effect, speed change, time delay of hydrophone, and the other factors can also lead to the frequency shift of LOFAR spectrum[8]. As a consequence, the passive sonar signals are not stationarity, and the result of detection and classification with LOFAR spectrum is not ideal, against background noise[9]. Therefore, we propose a feature extraction algorithm based on LOFAR spectral distribution (FELSD), in order to reduce interference of background noise and frequency shift, and to improve the performance of underwater acoustic target on classification eventually.

The accuracy of underwater acoustic target detection is directly related to the operational decision of marine vessels and their safety. With the development of silent running technology of submarine, it is more difficult to detect underwater acoustic targets, which leads to serious safety accidents (e.g., French and British submarines collide in 2009)[10]. Generally, the purpose of underwater acoustic target signal processing is to remove noise, improve signal gain, and restore acoustic signal weakening caused by various factors. In order to better detect, classify and track underwater acoustic target, scholars have proposed a series of models and algorithms of underwater acoustic signal, including signal correlation, adaptive noise cancellation, wavelet analysis, blind signal processing, various nonlinear processing techniques, and so on[3, 8, 10, 11].

Jahromi, et al.[3] presented an improved spectrogram based on the windowed fractional-Fourier transform of the acoustic signal with the optimal FrFT rules, and proposed a parallel combination method to enhance the reliability and stability of passive sonar system for classification.

Yin, et al.[8] presented a deep sound feature extraction network based on VGGNet, and proposed an underwater acoustic target classification framework based on CNN and LOFAR spectrum. Compared with traditional methods, their classification framework got a satisfactory result in real data sets of civil vessels, achieved 96% averagely.

Ren, et al.[10] presented a time-delayed neural-network-based classification system for comparing the recognition effects of different features, and then proposed a new feature extraction method based on wavelet packet component spectrum. The experimental result on the real dataset of two type of vessels indicated that the proposed method had a high recognition accuracy by selecting appropriate feature.

Li, et al.[11] proposed a method for target automatic detection and tracking of multiple frequency line spectrums in LOFAR based on HMM (Hidden Markov Model). Experiment indicated that, their method got an effective detection result on multiple time-varying frequency lines of underwater acoustic signals, which providing better multiple frequency lines sensing ability.

Despite these methods can effectively extract underwater acoustic signals, their detection effect is not ideal when the underwater target is affected by Doppler effect or speed changes. On the other hand, due to the complexity of background noise in underwater environment, it is easy for background noise to cover the radiated noise during feature extraction. This paper focuses on LOFAR spectral distribution, so as to effectively detect and classify underwater acoustic targets with the complex noise background and radiation noise frequency shift.

2. Felsd Algorithm

This section presents the FELSD (feature extraction based on LOFAR spectral distribution) algorithm, which encodes the LOFAR acoustic signal according to the sparse spectral characteristics of the LOFAR dataset. Traditional detection algorithms ignore the effect of frequency shift on classification performance generally, while our algorithm focuses on the sparse distribution characteristics of the dataset. Specifically, we take the independent spectrum characteristics and the degree of sparsity as the coding basis, which can reduce the influence of frequency shift and background noise on the feature extraction. In order to achieve such goal, FELSD algorithm is detailed described in the rest of this section.

The data collected by the hydrophone array are audio data, which are WAV format files. For the convenience of analysis, audio data need to be preprocessed into LOFAR spectrums. In this process, the audio files are processed into LOFAR spectrums through STFT (Short time Fourier transform). In addition, considering the confidentiality of the data, LOFAR spectrums are encrypted by fully homomorphic encryption algorithm (not necessary).

FELSD is mainly based on the sparse distribution of independent frequency components in the dataset, and uses the Gamma distribution and Beta distribution to calculate the down sampling distance to weaken the influence of frequency shift and background noise on the feature extraction of samples.

(1)The frequencies of LOFAR spectrums (the dimensions of n signals are all m) are converted into a one-hot matrix MatFrq, whose shape is (m, n). In the same way, the amplitudes of LOFAR spectrums are converted into a one-hot matrix MatApt, whose shape is same with MatFrq.

(2)The Beta function is used to calculate the sparse degree Sd of the matrix MatFrq, as equation(1) shown:

$$Sd = 1 + beta\left[0.5,\ Avg_{non-zero}(n),\ Avg_{zero}(n)\right] \tag{1}$$

where beta[*] denotes Beta probability density function, Avgnon-zero(n) denotes the mean of the total number of nonzero values of n signals, and Avgzero(n) denotes the mean of the total number of zero values of n signals.

(3)The Beta function is used to calculate the Gamma distribution Gd of the matrix MatFrq, as equation(2) shown:

$$Gd = gamma\left[\frac{0.5*(m+1)}{n*\pi^{m}},\ \frac{Sd}{m}\right] \tag{2}$$

where gamma[*] denotes Gamma distribution.

(4)Down sampling distance Dd is calculated with Gd, as equation(3) and equation(4) shown:

$$Itv = \frac{\sqrt{\sum_{i}^{I} X_{\max}^{2}(i) - \sum_{j}^{J} X_{\min}^{2}(j)}}{|I-J|} \tag{3}$$

$$Dd = Ceil[(Itv * FreR * Gd)^{2}] \tag{4}$$

where Xmax and I respectively denote the sample with the maximum sum of squares among n signals of the matrix MatFrq and the number of nonzero values among them, similarly, Xmin and J denote the corresponding sample and the number of nonzero values respectively, FreR denotes the refresh rate of passive sonar system, and Ceil [*] denotes the ceiling of * as an integral.

(5)After calculating the sampling distance, the matrix MatFrq can be recoded into matrix Mat as equation(5) shown:

$$(\ ,\ ) = Mat_{Frq}(\ ,\ ) / / Dd \tag{5}$$

where MatFrq(i, j) denotes the value of the i row in j column, the operator "//" denotes floor division, and encoder(i, j) denotes the result of recoding by Dd.

(6)When recoding the MatFrq matrix, some frequencies, which have closer values, will be encoded as the same result. Therefore, duplicate values in the matrix MatFrq are deleted (only the Kth number of duplicate values is retained, and K is the index value in the middle position of the same value), and the corresponding amplitudes in the matrix MatApt are also deleted. In addition, the reserved amplitude is adjusted as shown in equation(6):

$$amp(i) = amp_{raw}(i) * [1 - \frac{1}{1+\ln(N_{dup})}] \tag{6}$$

where ampraw(i) denotes ith reserved amplitude, and Ndup denotes number of duplicate values of ith adjustment.

(7)With the processing of step(6), the sparse matrix MatApt becomes denser than before. To ensure the validity of subsequent processes, the zero values in the matrix MatApt are replaced by a small constant, 10-6. Each signal u in MatApt is extracted, as the new feature of the raw signal X, finally.

3. Experiments

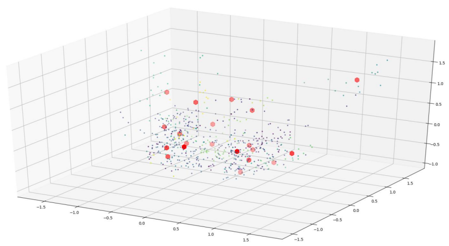
In this section, FELSD is evaluated from the two aspects of unsupervised and supervised classification. The raw LOFAR data and three recent methods, FrFT[3], VGGNet[8], and TDNN[10] are used for comparing with the proposed algorithm in accuracy and time loss. The experiments are based on a real dataset, which dataset used has been processed by STFT and fully homomorphic encryption algorithm. The description of the dataset is list in TABLE 1:

Table 1: Dataset description.

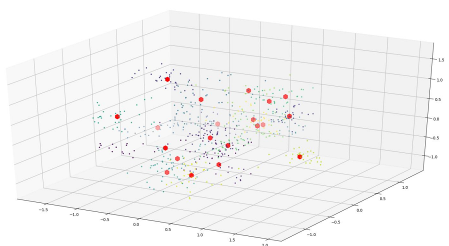
Frequency range (Hz)	Amplitude	Fresh rate (Hz)	Number of instances	Samples in each category
[DC-5000]	[0-1]	21	600	30

4. Unsupervised Classification

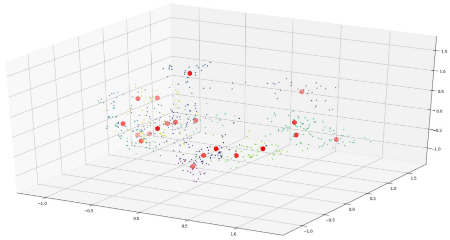
We test the feature extraction performance of FELSD and FrFT in clustering analysis with BIRCH (Balanced Iterative Reducing and Clustering using Hierarchies) [12]. In order to visually show the performance difference between the compared algorithms, PCA algorithm is used to reduce the dimension of the features into 3 dimensions. In addition, we also apply PCA algorithm and BIRCH to raw LOFAR data, so as to compare the difference in spatial distribution of the dataset before and after feature extraction. The results are shown in Figure 1:



(a) Raw lofar.



(b)Frft.



(c)Felsd.

Figure 1: Clustering results of raw lofar (a), frft (b) and felsd (c).

As is shown in Figure 1(a), the red sample points are the cluster centers, raw LOFAR data are distributed relatively denser in the middle region, and the boundary between each class cluster is not obvious, while distribution of sample points within the same cluster are dispersed. The accuracy of BIRCH to raw LOFAR data is 43.0%. In Figure1 (b) and (c), after feature extraction by FrFT and FELSD, the sample points are distributed balanced relatively in space. By comparison, our algorithm has larger distances between classes, which is more suitable for clustering analysis. The accuracy and time loss of FrFT and FELSD are 86.8% and 876 milliseconds, 99.3% and 954 milliseconds respectively, which further proves the effectiveness of our algorithm.

5. Supervised Classification

We then test the supervised classification performance of VGGNet, TDNN and FELSD-SVM, which is combined FELSD with SVM[13]. The dataset is divided into 80% training set and 20% test set, and the average of precision, recall, F1-measure and time loss of 5-fold cross validation are shown in Table 2:

Table 2: Dataset description

	VGGNet	**TDNN**	**SVM**	**FELSD-SVM**
Precision	0.83	0.76	0.56	0.93
Recall	0.86	0.71	0.43	0.88
F1-measure	0.84	0.73	0.49	0.90
Time loss(Second)	1.67	2.33	0.98	1.88

As is shown in Table 2, compared with VGGNet, TDNN, our algorithm has better performance in classification. Moreover, FELSD-SVM significantly improves the classification accuracy of SVM, despite the time loss of FELSD is slightly higher than VGGNet and SVM, it is acceptable compared with improved performance.

6. Conclusions

The detection and recognition of underwater targets is a great challenge because they cannot be directly observed by optical signals. Although some traditional algorithms are effective in detecting underwater acoustic targets, they are difficult to eliminate the affection of frequency shift and background noise. On the other hand, due to the particularity of underwater targets, although some underwater acoustic signals can be collected, their categories are unknown. As a result, some supervised classification algorithms or models are difficult to function.

In this paper, we proposed an effective algorithm for feature extraction based on LOFAR spectral distribution. With our algorithm, features of LOFAR spectrum can be extracted quickly and efficiently, and used in supervised and unsupervised models. Accordingly, experiments showed the effectiveness of proposed algorithm, which reflected its application value. In the future research, we will continue to study effective methods for LOFAR similarity assessment and DEMON feature extraction.

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